Detecting Creativity in an Open Ended Geometry Environment

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ABSTRACT

Creativity is a dynamic process which generates ideas that are both novel and of value. However there is little understanding in what drives creativity in students and how to help teachers or education experts to detect creative thinking. This paper begins to address this gap by providing a platform and experiments for studying how creative outcomes can ensue over time. The platform is an open ended environment for creating geometrical shapes that supports exploration and trial and error. We show that participants exhibit diversity in their usage patterns in the system, and in particular, some exhibiting 'creative leaps' in which they move from creating a sequence of shapes in one category to another, new category. We designed a visualization tool that aids understanding in detecting these aspects in students' work. We provide a basic computational model that is able to predict whether a student will create a new shape at a given point in time. The impact of this work is in beginning to provide tools for promoting creativity in students and directing their interactions in a way that facilitates the creative process.

Keywords

Creativity, Divergent Thinking, Geometry, Geogebra

1. INTRODUCTION

There is multiple evidence that exhibiting creativity in the classroom is linked to positive learning gains, and using educational technology to bring about creativity is an active area of research [19, 8]. To date, however, such technologies have relied on human teachers to detect and to promote creative behavior. While research on adaptive technologies for education have flourished, there are few studies on automatically detecting creativity from students' interactions.

This paper begins to address this gap by providing a platform for studying and computationally modeling creative tasks. The task requires participants to create geometric shapes and explore multiple solutions in a domain that is simple to define and explain, while still providing a rich space of possible solutions.

The task was chosen so that there is no single correct answer, and the goodness of a solution is measured by the number and quality of the different answers. This task supports a process of exploration and discovery. There are many possible strategies for solving the tasks, some requiring more skills than others.

We study people's search trajectories in the space of possible solutions, showing that people exhibit creative leaps [9], alternating between clusters of solutions and exploration. We adapt a model by Leikin [10] for measuring creative outcomes in users' interactions, based on defining their work in terms of flexibility, originality and fluency. We provide a visualization tool that decomposes a user's interaction sequence in the system to separate sequences of solutions. When a creative leap occurs, the solutions in the inferred sequence belong to the same class.

We show that people's creative outcomes in the system varies widely, in a way that depends on the creative leaps that are exhibited by the participants. We built a computational model that attempts to predict whether or not a given shape is new for a given participant. We define several sets of features that include statistics about shapes created as well as GUI operations used to create the shapes. The best performance was achieved by a random forest classifier that was based on both features.

These results can potentially inform the design of algorithms for detecting and promoting creative outcomes.

The remainder of this paper is organized as follows. In the next section we provide a general description of the creativity testbed for creating geometric shapes. We then describe a tool for visualizing the shapes created by individual users over time, and how to cluster these shapes in a way that can detect creative leaps. Finally we provide a computational model for detecting new shapes in a user's interactions, and discuss ways to extend this model to detect creative outcomes.

2. RELATED WORK

Previous research showed that creativity is linked to positive learning gains, and using educational technology to bring

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about creativity is an active area of research [19]. While these programming environment support interactions that can lead to creative thinking, they rely completely on human teachers to detect and to promote this behavior.

We focus on the use of technology to promote divergent thinking, which is a type of creative ability that generates multiple answers to problems [18, 6]. Guilford [6] defines divergent thinking as generation of multiple answers to a problem. Torrance[17] defined fluency, flexibility, novelty, and elaboration as parameters that describe divergent thinking. Fluency is the ability to create large number of ideas for a problem that are useful. Flexibility is the ability to change direction, thinking strategies and point of views. Originality is the ability to generate novel and unconventional ideas. Unconventional ideas defined as statistically infrequent.

There are several works focusing on the use of technology to promote creative outcomes in students. Multi Solution Tasks (MST) is mathematics open ended problems with multiple correct answers that can reached in different ways [12]. MST improves the participant's understanding and the connection between his knowledge domains, skills and strategies [4]. Levav-Waynberg & Leikin [12] found that MSTs raised the connection between knowledge domains in geometry, and improve the fluency and flexibility of the participants. Geometry plays a major role in Math teaching. It includes visual, abstract and logical skills. Geometry created opportunities for investigation, generalization, deduction and gives autonomy to the learner to explore mathematics with his personalized preferences [12, 3].

Sophocleous & Pitta-Pantazi [16] found that using software environment for geometry enhanced the creative abilities of students by facilitating them to provide more, different and unique solutions.

Noy et al. [15] demonstrated the role of creative leaps in two dimensional geometry. They show that human players exhibit two types of exploration: 'scavenging', where similar shapes are accumulated, and 'creative leaps', where players shift to a new region in the shape space after a prolonged search. They show that the network of shapes created by human participants is different from the class of networks created by applying a simple random-walk algorithm. We extend their work in two ways. First by providing a computational model to detect new shapes; second in extending the notion of creative leaps to a framework that allows a richer set of actions to be created. In subsequent work they studied creative exploration using a scale invariant model that considers relative changes in signals [7].

There are few studies on automatically detecting creativity from students' interactions. An exception is Manske and Hoppe [14], who have used supervised learning methods to detect creativity in programming assignments that require mathematical skills. They combined low level features (e.g, code snippets) with higher level features (e.g., the use of recursion, number of lines of code) to train numerical predictors and predicted a creativity score for new solutions. Chuang et al.[2] used fuzzy logic to detect student's creativity measures in a gaming environment. Loveless et al.[13] studied the use of technology to promote aspects of creative thinking for student teachers, including the development of new ideas, modifying and evaluating the originality and value of work as it develops. These works relied on manual approaches for detecting creativity and did not study how to visualize these creative outcomes.

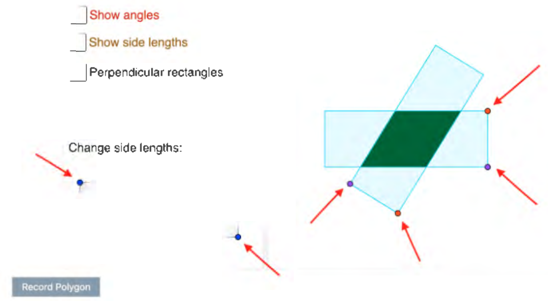

Figure 1: Open Creativity App

3. THE GEO CREATIVITY TESTBED

We designed an activity (built as a GeoGebra app) in which participants create geometric shapes by manipulating the shaded area that intersects two rectangles (See Figure 1).

Participants can employ geometric transformations on each rectangle according to several possible actions supporting by the testbed GUI: Translation (shifting a rectangle along the x or y axis), rotation (re-positioning the rectangle by changing one or more of its angles), re-sizing (increasing or decreasing the size of both of the rectangles). Creating different shapes requires to master different skills. It is easier to create polygons of varying number of sides by rotating the rectangles, but other types of shapes requires more steps, using more actions or have a precise positioning of the rectangles in designated angles.

To help with the positioning, participants can optionally choose to display the angels formed at the vertices, the length of the intersection shape sides, or position the two rectangles perpendicularly one to each other. At any point in time, participants can choose to submit their shape to a gallery. When the shape submitted to the gallery, the interface doesn't change and the participates continue their work from the same point.

The GUI design supports several key factors that have been shown to facilitate creative outcomes in students. First, it provides an open ended task in which there is no single correct answer, and the goodness of a solution is measured by the number and quality of the different answers [10].

Second, the task supports a process of exploration and discovery. Participants can manipulate two rectangles to create new shapes. Trial and error is a key part of the exploration process [5].

Third, understanding the task does not rely on complex or unique tool set. Participants with little knowledge in geometry can use the task and think about novel and useful categories. Participants with more knowledge and experience will have a better potential to think about new and

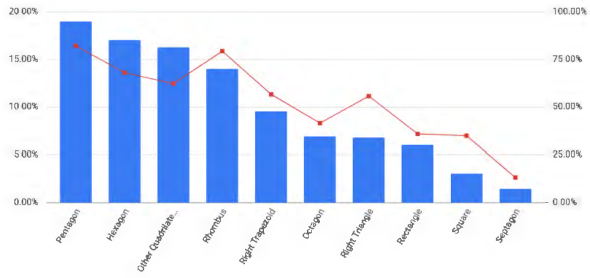

Figure 2: Categories Distribution over Participants

unconventional categories [1].

Fourth, there are many strategies to create shapes from the same category. Some requiring more skills or using more tools than others. For example, squares can be created by rotating and positioning the two rectangles, and also by using "perpendicular rectangles" option in the GUI menu [1].

This task is recommended activity by content developers for K4-K5 students that learn geometry. The idea is for students to learn to generate geometric shapes in a novel way (intersecting the two rectangles). The number of possible shapes that students can create with the system is not bounded.

3.1 Procedure

We recruited 183 Participants (87 undergraduate students and 96 Mturk workers with varying educational background - high school, Bachelor and master graduates). All participants needed to pass a tutorial and comprehension quiz about the study in order to participate.

All participants were requested to "create as many different polygons types as possible by intersecting two rectangles." Students performed the task as part of an extracurricular activity and were not monetarily compensated. Participants in Mturk received monetary compensation as follows: 30 cents as a show up fee and 10 cents for every type of shape that they've created.

The task was limited by 10 minutes, and on average participants spent 4.5 minutes on the task.

Participants created between one and ten different shape categories (e.g., Polygon, square, etc.) and 1445 shapes in total. Figure 2 shows the frequency of the shape categories submitted by users to their portfolio. The x axis denotes the shape category; the blue bars display the number of shapes that was created for each category (values in the left vertical axis). The red line shows the percentage of participates that created shapes of the given category (values in the right vertical axis.

As shown by the figure, the most popular shape categories were Pentagon, Hexagons and "other" Quadrilaterals (quadrilaterals which were not rhombus, square or rectangles). The least popular shape categories were septagon, square and rectangles. There was a general correspondence between the number of times a shape was created and the number of users who created the shape. However, some shapes categories, namely Rhombus, square and rectangle, were more popular. For example, the Rhombus is the fourth most popular shape category, yet it is the second most popular shape among the users. We will show later that these shapes played a special part in people's creative process.

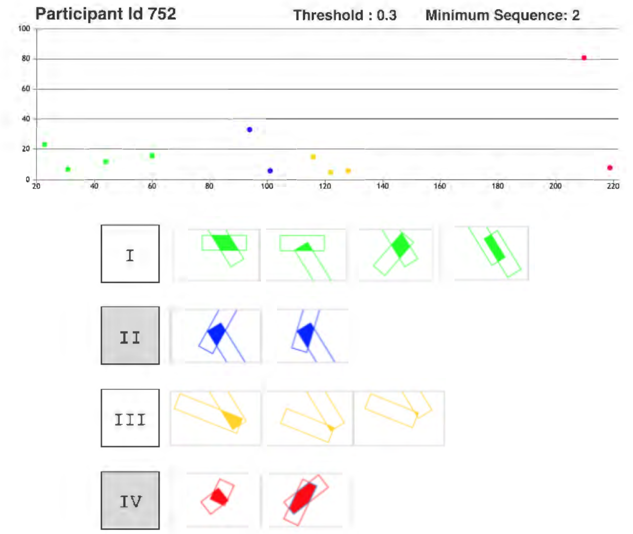

Figure 3: Visualization tool showing timeline of shapes (top), and shape sequences (bottom) for user ID 752

3.2 Visualization Tool

We designed a visualization tool for studying how individual participants create shapes over time. Fig 3 shows the main interactive panel in the visualization system. The main panel shows the shapes created by an individual user (ID 752). The x axis represents time (in seconds) from commencement of the interaction, while the y axis represents the length of time (in seconds) it took to create shapes. For example, the coordinate $(30, 4)$ shows the first shape created by the user (Rhombus) at time 30 and took 4 seconds to create. As shown in the figure, participant ID 752 created 11 shapes over a time span of 230 seconds. We can see that the participant exhibited high variance in the creation time of the shapes. For ease of analysis, there is a way to group shapes into temporal sequences according to the following criteria: First, a sequence has to include at least n contiguous shapes. Second, the probability that the next action belongs to the same sequence is greater than a designated threshold T. The threshold can be set in a way that maximizes the number of shapes in the sequence. A shape i commences a new sequence if $P(\frac{\Delta_i - \mu}{\sigma}) > T$ where Δ_i is the length of time spent to create shape i, μ and σ are the average time and standard deviation for creating shapes by the participant. In this way we consider the extent to which the creation time of each shape agrees with the individual participant (assuming a normal distribution over creation time).

Figure 3 shows four shape sequences that were created by the user, inferred by the criteria described above. We can see that sequence II and IV are relatively short and include shapes that share a common category (that of trapezoids or

hexagons, respectively). In contrast, sequence I and III are longer and include shapes of different categories. We next show how these sequences yield insights into creative aspects of the shape creation processes.

3.3 Measuring Creativity

We measure the creativity of a participant following Torrance [17] who defined dimensions of flexibility, fluency and originality to describe creative solutions to problems: Fluency is the number of solutions that was proposed by the participant. Flexibility is the number of strategies that the participant applies for the solution. Originality is statistically infrequent ideas that were produced by students relative to their classes or groups.

We calculate the score by the formula suggested by Leikin [11], adapted to the geometry app. The flexibility of a shape i is 10 if the shape is new for this participant, or 1 otherwise. The originality of a shape i is 10 if the shape was chosen by fewer than 15% of participants (septagons), 1 if the shape was chosen by between 15% and 40% of participants (rectangles and squares), and 0.1 if the shape was chosen by more than 40% of participants.

The fluency of a shape is always 1. Let n be the number of shapes created by the participant (also the participant's fluency score). The creativity score of a participant is computed as $\sum_{i=1}^{n} FX_i \cdot OR_i$ where FX_i and OR_i are the flexibility and originality of shape i.

4. CREATIVE LEAPS

Participants exhibited a diverse range of creativity scores in their work. The average score was 80 with a standard deviation of 54. To explain differences between students, we need to analyze the dynamics of how shapes were created. We will distinguish between two types of shape creation, those representing exploration in the space of possible concepts, and those representing exploitation of one of the concepts that is used to create shapes.

Koestler [9] describes a creative leap as the moment where a new dimension of possibilities appears. The creative leap signifies a point in the search space in which the learner discovers a new class of solutions and begins to exploits this space by creating shapes.

In sequence II and IV of participant 752 (shown in Figure 3) the participant exploits the concept of trapezoid and of hexagons, completing two shapes in each category. Both of these sequences represent creative leaps. In contrast, sequence I and III for this user represents exploratory behavior in which the participant does not converge on a shape category. In particular, sequence IV commenced 81 seconds after the last shape, suggesting a lengthy process of exploration leading to the next shape category.

We use the concept of creative leaps to distinguish between different types of participants, as determined by their interaction in the system.

Another example, participate 651 holds an MA degree, exhibited a creativity score of 128, with fluency of 36, flexibility of 8, and originality of 1 (rectangle and square). Participant

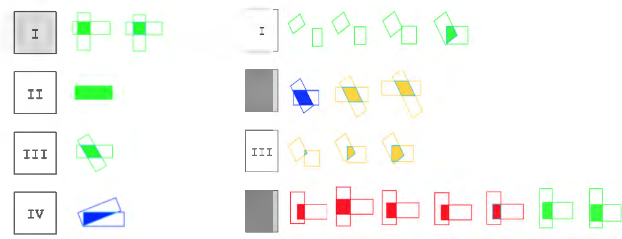

Figure 4: Shape sequences for low scoring participant ID 655 (left) and high scoring participant ID 651 (right)

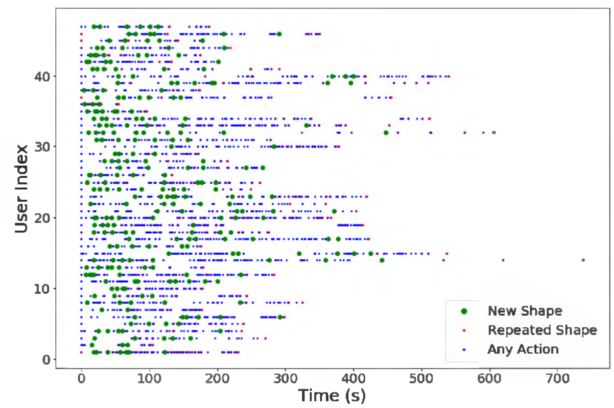

Figure 5: New and old shapes

655 holds a high school diploma, with a creativity score of 61, with fluency of 5, flexibility of 4 and originality of 1 (rectangle and square).

Figure 4 shows the shape sequences for these two participants. As shown by the figure the users exhibited drastically different interaction styles with the system. The low scoring participant (user ID 655) created only five shapes, which can be described by 4 sequences. Only sequence I for this user consisted of shapes of a similar category. In contrast, the high scoring participant (user ID 651) created 36 shapes, which can be described by 10 sequences (for brevity we only show the first four). Five of these sequences included shapes with particular categories.

5. COMPUTATIONAL MODEL

Using the creation of a new shape as a proxy for creativity, we build a computational model that attempts to predict whether or not a given shape is new for this participant. This is a first step for detecting creativity for this participant. To this end, we extract a number of features and use logistic regression and a random forest classifier to predict the binary outcome of whether or not a given shape is new for the user.

Figure 5 shows the layout of new shapes (green) and old shapes (blue) for users across time. It demonstrates that while the proportion of new shapes being generated certainly does decrease as the user continues to interact on the platform, there are a significant number of shapes that are created 'later' on in the user's interaction session. These shapes

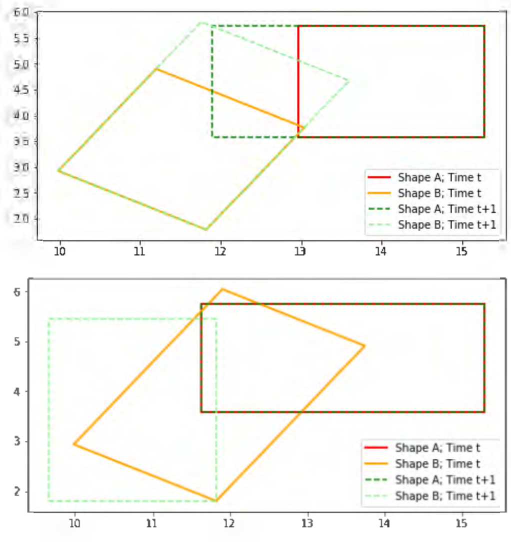

Figure 6: Plots showing the raw shape coordinates and the extracted actions from the database. Top is a resize action where both input rectangles are affected. Bottom is a rotation action to the second rectangle

are new to the user and can signify the commencement of a creative leap.

5.1 Feature Extraction

The raw data represents individual coordinates of the two input rectangles where the user can rotate, translate and resize the two rectangles. We extract changes to these coordinates to represent the 5 actions that the user can perform on the system. Figure 6 shows the primary actions that a user can perform. The resize action affects both shapes simultaneously whereas the user can perform rotate and translate actions to each shape individually.

As a number of actions are preformed before a user submits a shape, we include the history of actions in the feature matrix considering a maximum of 15 actions before the shape was submitted; 95% of shapes were submitted with less than 15 steps. We aim to infer whether including the history of actions provides additional information to a model predicting the creation of a new shape. In other words, our goal is to determine if combinations of actions are predictive of a new shape and thus indicative of certain creative insights.

5.2 Method

Given four feature sets, we use cross-validated logistic regression (LR) and random forest (RF) classification to predict the binary classification problem of whether or not the shape is new for the user. Other classification techniques were explored including support vector machines, boosted decision trees and naive Bayes classifiers but LR and RF were chosen for simplicity and the ease of interpretation into the parameter coefficients (or feature importance in the RF). Moreover, LR allows the application of an L1 sparsity regularizing parameter to induce sparsity in the feature space (thereby assisting inference). The available features are:

Table 1: Different combinations of available features that the four feature sets used.

Feature Set	Shape History	Action History	Aggregated Action History
Feature set 1	Y		
Feature set 2	Y	Y	Y
Feature set 3	Y		Y
Feature set 4	Y	Y	

1. **Shape History**. Counts of previously submitted shapes from the user for each of the 10 shape categories.

2. **Action History**. A one-hot encoded representation of actions in 15 previous steps leading into the shape creation. Following the actions shown in Figure 6 there were 3 possible actions (translate, rotate or resize) at each step. We further include a 'control' action that represents a recorded step but no action. This case might occur when the user does not interact with the shapes but rather interacts with a different UI element or possibly performs an administrative action such as submitting the shape. This creates 60 features in total for each instance.

3. **Aggregated Action History**. The sum of the **Action History** features across the 15 steps. This results in 4 additional features per instance describing the number of times each action was performed. For example, a vector $(2, 3, 5, 5)$ corresponds to 2 translate, 3 rotate, 5 resize and 5 control actions (in any order).

The three sets of available features were aggregated in different combinations to provide four feature sets that were used for evaluation. Table 1 summarizes the different combinations that were used.

5.3 Results

Our goal was to determine if certain sequences and/or combinations of actions are predictive of the user generating a new shape. Table 2 summarizes these results. We note that the Feature Set 3 provides a slight improvement over the baseline of Feature Set 1 for both LR and RF. Feature Set 4 with RF shows the greatest accuracy with a 2% increase over the baseline feature set. The results are reported from a 10 fold cross-validation but the predictive increase is not significant across the folds. The results suggest that the inclusion of the action data does assist slightly with the predictive performance of the model but we note the result is not conclusive. However, analyzing the feature weights of the LR for Feature Set 3 and the RF for Feature Set 4 is illuminating.

It is interesting to note that the RF model with the temporal features outperforms the LR on these same feature sets. Again, although the results are not significant they do suggest there is a more complex interaction of the action history of the user that might be predictive of the new shape creation. Further investigation into how **sequences** of actions might be indicative of the creation of a new shape (and thereby indicative of a creative leap) is needed to answer this question definitively.

Table 2: Table showing the results from the prediction task of predicting a new shape for a given user.

Feature Set	Accuracy LR	Accuracy RF
Trivial all 0 prediction	59.9%	59.9%
Feature set 1	75.5%	75.4%
Feature set 2	74.8%	76.1%
Feature set 3	**76.0%**	76.5%
Feature set 4	73.5%	**77.5%**

6. CONCLUSION AND FUTURE WORK

We presented an approach for studying creativity using a web based tool in which participants created geometric shapes. This task supports a process of exploration and discovery, allowing people to exhibit creative leaps in which they transition between different areas of the search space of possible solutions. We adapted a model by Leikin for measuring creative outcomes in users' interactions. We collected data from multiple people interacting with the system showing that they vary widely in terms of the creativity they exhibit. We built a visualization tool that decomposes a user's interaction sequence in the system to separate sequences of solutions. We built a computational model that attempts to predict whether or not a given shape is new for a given participant. We define several sets of features that include the number and categories of shapes that were created by the user, as well as basic actions performed by the users in the system for a window of activity. The best performance was achieved by a random forest classifier that was based on both features. In future work we intend to extend the computational model to detecting creative outcomes in new types of domains.

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